Deceleration of the Trend in Inequality of Educational Outcome
in the Netherlands*

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1 Introduction

The association between family socioeconomic status and the offspring’s educational attainment has long been studied in social stratification and social mobility research (for example Breen and Jonsson, 2005; Hout and DiPrete, 2006). A strong positive association means that people with a high socioeconomic background are more likely to achieve higher levels of education than people with a low socioeconomic background. The strength of the association is for this reason often referred to as educational inequality. In this article I will focus on the association between socioeconomic background and the highest achieved level of education. Following Buis (2008a), the association between social background and highest achieved level of education will be called Inequality of Educational Outcome (IEOut) in order to distinguish it from the association between highest social background and the probabilities of continuing from one level of education to the next, which is referred to as Inequality of the Educational Opportunities (IEOpp).

This article will have a primary and a subsidiary aim: The primary aim is to provide a detailed description of the trend in IEOut in the Netherlands between 1912 and 1988. Previous literature has found for the Netherlands that IEOut decreased linearly over time (De

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Graaf and Ganzeboom, 1990, 1993; De Graaf and Luijkx, 1995; Ganzeboom, 1996; Sieben et al., 2001). Such a linear decrease in the association between socioeconomic background and highest achieved level of education is unlikely to continue. A linear trend would eventually lead to a negative association between socioeconomic background and highest achieved level of education, which would mean that having a high status background would become a hindrance instead of an asset for attaining education. This is so implausible that the negative trend in IEOut will have to slow down. So, the question that this paper tries to answer is: Has there been a deceleration in the trend in IEOut? In order to answer this question the effect of family background on highest achieved level of education (IEOut) is allowed to change over cohorts according to a smooth but flexible curve. The trend is the slope of this smooth curve (first derivative), and the change in trend is the slope of the slope of this curve (second derivative). To assess whether the negative trend significantly decelerated I will test whether the change in trend is significantly positive, since a slowing down of a negative trend means that the trend moves from more negative to less negative.

The subsidiary aim is to assess the susceptibility of data assembled in the International Stratification and Mobility File (ISMF) (Ganzeboom and Treiman, 2008), to three potential sources of error. The first potential source of error is due to the fact that the ISMF consists of multiple surveys. The variables of these surveys have been post harmonized and then stacked in order to create a single dataset. It is likely that the quality of a survey will influence the strength the associations between the variables in that survey, as the associations in low quality surveys will be contaminated by more noise than the associations in high quality surveys. If the quality of the surveys differs systematically over time then this would lead to a false trend in the effect of family background on education. The second potential source of error refers to the scale of education. The most commonly used scale in the Netherlands is approximately the institutional years of education with an *ad hoc* correction. Buis (2008b) proposed a scale with a stronger empirical foundation, which scales the levels such that education optimally predicts occupational status. The most prominent difference between these two scales is the *a priori* scale assigns too much value to lower vocational education. This can influence the estimated trend in IEOut as this difference in scaling means that the
estimated trend is likely to respond differently to changes in the proportion of respondents with lower vocational education over time. The third potential source of error is missing data. This will lead to biased estimates if the likelihood of not answering a question is related to the value of dependent variable. The dependent value is in this article the highest achieved level of education, and it is likely that the willingness and ability to finish a survey is associated with the respondent’s highest achieved level of education. So, it is plausible that missing data could cause bias in the estimates of IEOut. If the number of missing values changes over time, then the severity of this problem would change over time and thus also bias the estimated trend. The presence of these three potential sources of error is easier to detect when studying changes in the trend in IEOut, as this is a very delicate analysis. If the potential sources of error matter, then they will certainly show up in such an analysis.

2 Previous research

The challenge of studying the trend in IEOut is to cover a sufficient period of time such that the trend and changes in the trend become visible. A common strategy is to take multiple surveys and compare respondents that are born in different years, that is, the time is captured by comparing so-called synthetic cohorts. By comparing synthetic cohorts a single survey can cover a period of almost 40 years (by using respondents who are between 25 and 65 years old) and this period can be further extended by adding surveys collected at different times. These cohorts are used as a measure of when the effect of social background on educational attainment took place. This is reasonable given the strongly age stratified nature of full time education, which means that people born in the same year face a very similar educational system. Within the Netherlands this technique was first used for the study of the trend in IEOut by Ganzeboom and De Graaf (1989), and was used in numerous other studies since (De Graaf and Ganzeboom, 1990; De Graaf and Luijkx, 1992; De Graaf and Ganzeboom, 1993; De Graaf and Luijkx, 1995; Ganzeboom et al., 1995; Ganzeboom, 1996; Rijken, 1999; Korupp et al., 2000, 2002), and resulted in the International Stratification and Mobility File (Ganzeboom and Treiman, 2008). Five of these studies (De Graaf and Ganzeboom, 1990;
De Graaf and Luijkx, 1992; De Graaf and Ganzeboom, 1993; De Graaf and Luijkx, 1995; Ganzeboom, 1996) test whether the trend in IEOut in the Netherlands is linear or not, and none of these studies can reject the hypothesis that IEOut is linearly decreasing over time. This result has been largely reproduced using the same data as will be used in this article in (Buis, 2008c): The association between father’s occupational status and the respondents highest achieved level of education has declined linearly over time for both men and women. The same was true for the association between the father’s highest achieved level of education and the respondent’s highest achieved level of education for women, but not for men. The tests for non-linearity of the trend where in all cases performed by comparing a model with a linear trend with a model with non-linear trend. This non-linear trend was either a quadratic trend, or a discrete trend, where the period was broken up in a series of cohorts and separate IEOuts where estimated for each cohort. This could explain why no non-linearity where found, as quadratic functions can easily be too rigid to adequately represent a non-linear trend, while a discrete trend is very flexible but expends a lot of statistical power making it hard to find any significant evidence for non-linearity in the trend. The aim of this article is to find out if any non-linearity in the trend can be found if one uses a model that is more flexible than a quadratic function but less flexible than a discrete trend. Other limitations of these previous studies is that they do not take the three potential sources of error into account: the fact that the data consists of multiple surveys of differing quality, the presence of missing data, and the scaling of the levels of education. The subsidiary aim of this paper is the investigate whether this matters.

3 Data

The data consists of 55 surveys held in the Netherlands between 1958 and 2006 that where post-harmonized as part of the International Stratification and Mobility File (ISMF) (Ganzeboom and Treiman, 2008). Where available survey weights have been used. The weighted number of respondents is 86,581. The number of respondents is unequally distributed over the cohorts, as is shown in figure 1. Of these respondents 9,416 have missing information on
father’s occupational status, 651 on highest achieved level of education, and 342 on both. If
the proportion of missing information varies across cohorts then this could bias the estimate
of the trend. Figure 2 shows that this is the case. The reason for these differences across
cohorts could be in part an age-effect, as the older cohorts will consist mainly of people that
were old at the time of the interview, and in part be a period effect, which can refer to changes
in a general attitude towards surveys and the introduction of computer assisted interviewing
which makes it harder to skip questions.

[Figure 1 about here.]

[Figure 2 about here.]

The purpose of this paper is to investigate the change in Inequality of Educational Out-
come over time. Time is measured by the year in which the respondent is 12, which is the
age at which most persons in the Netherlands make the most important decision in their
educational career. Information is available for the cohorts 1912–1988. IEOut is measured by
the strength of the association between highest achieved level of education of the respondents
and their father’s occupational status. Father’s occupational status is measured in ISEI scores
(Ganzeboom and Treiman, 2003). The original ISEI score is a continuous variable ranging
from 10 to 90, but it has been has been standardized to have an overall mean of 0 and a
standard deviation of 1. The highest achieved level of education of the respondents is mea-
sured in either the original \textit{a priori} scale from the ISMF or in the empirical scale estimated
in Buis (2008b). A description of the different levels of education and the two scalings have
been reproduced in table 2. The first three columns show the name of each level, their En-
lish translation, and their classification in the ISCED (UNESCO, 1997) scheme. the fourth
column presents the institutional duration, or the number of years it would take a ‘standard
student’ to finish that level of education. The final two column present the two scales. The
most striking difference between the two scalings is the value of lower vocational education
(LBO), whose value is considerably overestimated in the \textit{a priori} scale. This could have an
impact on the estimated trend in IEOut, as changes over time in the proportion of respon-
dents with LBO will have different consequences for changes in IEOut in these two different
scales. The scales are in table 2 presented in terms of pseudo-years of education. In the
analysis these scales will be standardized to have a mean of zero and a standard deviation of
one.

[Table 1 about here.]

A key characteristic of this data is that it consists of different surveys. A major advantage
of this approach is that this greatly increases the period that can be studied because these
surveys were held at different times. This is illustrated in figure 3. It shows for each survey
the cohorts to which it contributes observations. It also shows that the oldest cohorts get
their observations from only a few (4) surveys, while others get their observations from almost
all surveys. So peculiarities of individual surveys are most likely to influence estimates in the
earliest cohorts, as in these cohorts each survey is responsible for a sufficient proportion of the
observations to have a noticeable influence. The characteristics of individual surveys are less
likely to have an effect on the estimates in the middle cohorts, as no single survey is dominant
in these cohorts. Table 1 gives an overview of the differences between the surveys. The first
two columns identify the surveys and relates the survey numbers in figure 3 to the full citations
in Appendix XX. The next two columns give information on when the surveys where held
and which cohorts are covered, and the fifth column identifies how many observations each
survey contributes to the entire dataset. The remaining five columns give some indication
of the quality differences between the surveys. It shows large differences between surveys in
the response rate, the number of missing values, and the detail in which the key variables
are measured. The response rate is missing for some surveys, because for some surveys the
response rate is no longer known, while for others the response rate is not informative as they
are waves in a panel.

[Figure 3 about here.]
Table 1: Surveys and indicators of their quality

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4 Method

The main aim of this article is to estimate a non-linear trend in IEOut and test whether the decreasing trend in IEOut has slowed down. The subsidiary aim is to investigate whether it matters if controls for three potential sources of error are included in the analysis.

For the estimation of the non-linear trend a two-step process has been used. First, a new dataset is created containing, for each annual cohort, an estimate of IEOut for men and women, and their standard errors. In order to make sure that each cohort contains enough observations the following combined cohorts are created: 1900/1901, 1902/1904, 1905/1907, 1910/1911. The estimates are obtained by regressing the respondent’s highest obtained level of education on father’s occupational status, separately for men and women and each cohort. Second, a smooth curve is fitted through these estimates of IEOut, but estimates with small standard errors, that is, measured with great precision, receive more weight than estimates
with large standard errors. These curves also provide estimates of the trend and the change in trend. These are the first and second derivatives of the smooth curve. The smooth curve that is going to be estimated through the estimated IEOut is a local polynomial curve (Cleveland, 1979; Loader, 1999; Fox, 2000).

The local polynomial curve provides new estimates for the level of IEOut for each cohort using information from nearby cohorts. For example, the point on the local polynomial curve for cohort 1938 is computed using the following four steps: First, the observations that will be used in the estimation are selected. This is typically done by selecting a fixed proportion, say 65%, nearest observations. This is shown in figure 4 in panel (a). Second, observations that are selected are weighted according to their distance from 1938. A common function used to create these weights is the tricube function\(^1\). The tricube function is shown in panel (b) in figure 4. The tricube weights ensure that cohorts close to 1938 receive more weight when estimating the value of cohort 1938. Third, these weights are adjusted in such a way that they take into account that some cohorts are estimated with much more precision then others. The raw estimates of IEOut are regression parameters, so an estimate of the precision of the estimate is available in the form of the standard error. Weights based on the inverse of the square of the standard error would properly correct for the difference in precision between cohorts. The weights based on proximity to cohort 1938 and the weights based on the precision of the estimates of IEOut are combined by computing the product of these two. This is shown in panel (c) of figure 4. Fourth, a regression of IEOut on cohort, cohort squared, and cohort cubed, is estimated using these combined weights. The predicted IEOut from this regression for cohort 1938 is the local polynomial estimate. It uses most information from cohorts that are close by and estimated with high precision, and less information from cohorts that are far away or are estimated with low precision. Furthermore, the slope of this regression line in 1938 is a local estimate of the trend, and the change in slope in cohort 1938 is a local estimate of the

\[ W = \begin{cases} 
1 - \left(\frac{|x-x_0|}{h}\right) & \text{if } \frac{|x-x_0|}{h} < 1 \\
0 & \text{if } \frac{|x-x_0|}{h} \geq 1
\end{cases} \]

\(^1\)If the cohort of interest, the ‘focal value’ is represented by \(x_0\) and the span (half the range that contains 65\% of the observations) by \(h\) then the value \(x\) is assigned the weight
change in trend in 1938. These are obtained by evaluating the first and the second derivative of the regression line at 1938. The entire local polynomial curve is obtained by repeating this process for all cohorts. This procedure is implemented in the \textit{locfit} package (Loader, 2005) in the R statistical computing environment (R Development Core Team, 2005). This also provides confidence envelopes for the curve, the first and the second derivative, using procedures discussed in (Loader, 1999).

Previous studies investigating changes in the trend in IEOut have used one of two strategies: Either they added interaction terms between parental background variables and time and time squared, or they added interaction terms between parental background variables and time as a series of dummies. The first strategy is usually not flexible enough to adequately fit the data. The second strategy is too flexible, which means that too much statistical power is lost making it hard to find any evidence for a non-linear trend. The method used in this article takes an intermediate position between these two methods, and is thus more likely to find evidence of a non-linear trend if it exists.

The subsidiary aim of this article is to investigate sensitivity of this analysis to the three potential sources of error: The first potential source of error is the fact that the ISMF consists of multiple surveys. The survey effects are controlled for by adding dummies for survey, and interacting these dummies with father’s occupational status. The dummies are constructed in such a way that the main effect of father’s occupational status represents the IEOut in an average survey, so differences between cohorts are no longer the result of differences across surveys. By adding survey dummies and interactions between the survey dummies and father’s occupational status, each survey has it’s own baseline IEOut, but the trend is constrained to be the same for all surveys. The reason for this choice was that there may be good reason to suppose that the quality of a survey can influence the effect of father’s occupational status on the respondent’s education, as the effect is likely to be smaller in more noisy data, but the effect of data quality on the estimated trend of the effect of father’s occupational status is much less clear.
The second potential source of error is the fact that there are multiple ways in which the dependent variable, the respondent’s education, can be scaled. The ISMF uses a common strategy by starting with the institutional years of education, the number of years a ‘standard student’ would need to finish that level of education, and apply some ad hoc correction to make sure that the ordering of levels corresponds with an a priori ordering. Buis (2008b) proposed an alternative scale based on the idea education predicts the occupational status of the respondent, and if education is better scaled then education should be better at predicting occupational status. This way one can estimate an optimal scale of education. These two scales where presented in table 2. By comparing the estimated trend using the a priori scale with the estimated trend using the empirical scale one can assess whether these differences actually matter.

The third potential source of error is the presence of missing data. The annual estimates of IEOOut are controlled for missing data using Multiple Imputation (Little and Rubin, 2002). The idea behind Multiple Imputation is to create multiple ‘complete’ datasets by first estimating for each missing value a distribution of plausible values, and then draw multiple values (in this case 5) from this distribution. This is done in Stata using the ice (Royston, 2004, 2005a,b, 2007) module. The model of interest is estimated on each ‘complete’ dataset. The point estimate is the average of the point estimates from the different ‘complete’ datasets, and the variance of the sampling distribution (the standard error squared) is computed according to equations 1 till 3 (Little and Rubin, 2002). Equation 1 shows that the variance of the sampling distribution \( (se^2) \) in case of \( m \) ‘complete’ datasets consists of two elements: The first element is described in equation 2, and is the average of the variances of the sampling distributions in the different ‘complete’ datasets. This represents an estimate of the degree of uncertainty about a parameter which ignores the fact that some of the data is itself uncertain as it consists of imputations rather than real observations. The second element in equation 1, equation 3, corrects for this by using the differences in the parameters \( (\beta_j) \) between the different complete datasets as a measure of the uncertainty due to the imputations.
\[
se^2 = \overline{se^2} + (1 + 1/m)B \tag{1}
\]
\[
\overline{se^2} = \frac{\sum_{j=1}^{m} se_j^2}{m} \tag{2}
\]
\[
B = \frac{\sum_{j=1}^{m} (\beta_j - \overline{\beta})^2}{m - 1} \tag{3}
\]

The key issue with multiple imputation is the model used for estimating the imputed values. This model must be at least as flexible as the model of substantial interest (Little and Rubin, 2002). For this reason separate imputation models are estimated for each combination of cohort and survey. Within each combination imputations for the missing values are created from a model using father’s and respondent’s occupational status and education, with interactions between whether the respondent is male or female and all these variables. The occupational status of the respondent and the level of education of the father are also used in the imputation model even though they will not be used in the final model of interest in order to improve the imputations. However, the father’s highest achieved level of education is only added when available, which was not the case in 10 surveys. Imputations where only carried out if the cohort-survey combination had at least 20 fully observed cases. As a result not all missing values where imputed. There were 9,758 missing values for father’s occupational status of which 1,934 could not be imputed, and there were 993 missing values for the respondent’s highest achieved level of education of which 181 could not be imputed.

5 Results

The results using estimates of IEOut while controlling for all the potential sources of error and using the empirical scale are shown in detail in figure 5 for men and figure 6 for women. Panels (a) show local polynomial curves fitted through the annual estimates of IEOut with their 95% confidence envelope. The confidence envelopes always remain above zero, indicating that the offspring of fathers with a higher status occupation did on average attain more education than the offspring of fathers with a lower status occupation. Panels (a) also show that the
level of inequality appears to have changed over time for both men and women. This is tested in the panels (b), which show the trend in IEOut, that is, the first derivatives of the local polynomial curves in panels (a). A period of significant negative trend is found for both men (1941–1960) and women (1952–1977). The hypothesis that the trend is zero in the last period (after 1960 for men and 1977 for women) cannot be rejected, suggesting that the trend has indeed slowed down. Notice however that the confidence envelopes are very wide for both the youngest and the oldest cohorts, so the finding of zero trend in the most recent cohorts could also be due to lack of statistical power. The way to solve that is to also estimate the changes in trends, the second derivatives, which are shown in panels (c). If the trend decelerated then the second derivative should be positive, indicating the negative trend became less negative. Panels (c) show a significantly accelerating trend (negative second derivative) between 1935 and 1944 for men and 1949 and 1952 for women, but no significant deceleration. For men the point estimates of the change in trend are positive before the trend became insignificant, providing some indication that the trend decelerated. For women the point estimate of the change in trend is also briefly positive prior to the trend becoming non-significant, but this period is much shorter, and quickly becomes negative again, so the case for a decelerating trend for women is much less convincing. These results are summarized in panel (d). The curve represent the smooth estimates of IEOut from panel (a), while the shaded areas below that curve represent the periods of significant trend and the shaded areas above the curve represents periods of significant change in trend.

Figures 7 and 8 show how controls for the three different potential sources of error influenced these results. Panels (a) and (b) use the a priori and the empirical scale of education respectively. Panels (c) show the trend using the empirical scale while controlling for survey effects. Panels (d) show the trend using the empirical scale while controlling form missing data. Comparing panels (a) and (b) shows that the scale of education does influence the estimated trend. A decelerating trend was found for men using the a priori scale, but this
became insignificant when the empirical scale was used. For women using the empirical scale leads to a significant positive estimates of the trend prior to the negative trend, and a significant transition between the positive and the negative trend. The aspect of the trend that remains largely unaffected by the scale of education is the downward trend during the third quarter of the twentieth century. The empirical scale will be used as the preferred scale, because the empirical scale does not overestimate the value of lower vocational educational education (LBO) and does not contain an *ad hoc* adjustment of the value of higher secondary vocational education (MBO). The panels (c) show the trend in the ‘average survey’, thus controlling for survey effects. This correction mainly affects the oldest cohorts. The likely reason for this is that these cohorts contain data from only a few surveys, as was shown in figure 3. As a consequence a problem in an individual survey could have an influence on the results. The younger cohorts contain data from many surveys, so any problems with individual surveys is likely to be averaged out. One important way in which surveys differ from one another is the number of missing values, as was shown in table 1. If this is the main source of differences in results between surveys then the trends in panels (d), which controls for missing data but not for surveys, should closely correspond to the trends in panels (c). However, the trend in panels (d) closely corresponds to the trends in panels (b), indicating that controlling for missing data hardly influences the results.

6 Conclusion

This article had a primary and a subsidiary aim: The primary aim was to provide a detailed description of the trend in IEOut in the Netherlands between 1912 and 1988, and in particular whether the negative trend in IEOut has decelerated. Previous studies all found a positive IEOut and an overall negative trend in IEOut, but failed to find any evidence that this trend was curved. This article did find evidence that the trend has been non-linear, but has not found the deceleration in the decreasing trend in IEOut that was expected. The most robust
findings in this article are a period of negative trend for both men and women (1941–1960 and 1952–1977 respectively), which was preceded by a period of accelerating trend (1935–1944 for men and 1949–1952 for women). The presence of the period of accelerating trend indicates that previously the trend was less negative, and for men there is solid indication that the trend was even positive. There is some evidence that the negative trend decelerated prior to becoming insignificant for men, but this deceleration is not significant. There is no indication that the negative trend for women decelerated prior to becoming insignificant, indicating that the lack of significance of the negative trend in the youngest cohorts has more to do with lack of power than with a lack of negative trend.

The subsidiary aim of this article was to use this analysis to investigate the degree of susceptibility of the International Stratification and Mobility File (ISMF) (Ganzeboom and Treiman, 2008) to three potential sources of error: the scaling of education, survey effects, and missing data. Controls for missing data did not change the results, but both controls for survey effects and using different scales of education did moderately influence the estimated trend. All analyses resulted in a negative trend in IEOut during the third quarter of the twentieth century for both men and women and most analyses found that the negative trend was preceded by an acceleration of the negative trend (the exception was the analysis for women using the \textit{a priori} scale). Controls for survey effects primarily influenced the older cohorts, for both men and women, while different scalings of education primarily influenced the estimated trend in older cohorts for women.

The three potential sources of error investigated in this article are not the only problems that can plague this data. An important set of problems depends on the ways time is measured using synthetic cohorts, cohorts that are observed in a cross-sectional survey. There are two problems associated with the use of synthetic cohorts. The first problem is that a synthetic cohort is not a proper sample from the population of people born in a certain year, but a sample from the population of people born in a certain year \textit{and} who are still alive and living in the Netherlands at the time the survey was held. This can be a problem for cohorts that are very old when the survey was held because in these cohorts higher educated respondents are likely to be over-represented, as higher education person are likely to live longer. Such
selection on the dependent variable can bias the results (Breen, 1996). This is solved in this article and in other studies by only using respondents younger than 65 years old. This way not enough people will have died for this to become a problem. The second problem with synthetic cohorts is that education happens over a period of time, so it is not exactly clear which historical period is represented by a cohort. A reasonable choice is to look at the time when the respondent was 12 as in the Netherlands that is the age when people make the most important decision in their educational career, but any such choice will necessarily be approximation. This is particularly relevant when studying the consequences of a policy change, as synthetic cohorts will only approximately classify the respondents as being affected or not affected by the policy change. A careful analysis of these issues could be a valuable complement to the present study.

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Figure 1: Number of observations per cohort
Figure 2: Proportion of missing values per cohort

![Proportion of missing values per cohort](image-url)
Figure 3: Cohorts covered by different surveys (survey numbers correspond to table 1 and are ordered by the year in which the survey was held)
Figure 4: Obtaining local polynomial regression estimate for IEOout for cohort 1938, adapted from figure 4.1 from (Fox, 2000, p. 24–25)

(a) Observations Within the Window
span = 0.65

(b) Tricube Weights

(c) Tricube (+), Precision (x), and Joint (o) Weights

(d) Weighted third degree polynomial (weight is the area of the symbol)
Figure 5: Trend in Inequality of Educational Outcomes and change in trend for men. (IEOut is measured as standardized regression coefficients. The local polynomial smooth has a span of .65 and uses weights proportional to the inverse of the variances.)
Figure 6: Trend in Inequality of Educational Outcomes and change in trend for women. (IEOut is measured as standardized regression coefficients. The local polynomial smooth has a span of .65 and uses weights proportional to the inverse of the variances.)
Figure 7: Trend in Inequality of Educational Outcomes and change in trend for men while using different scales of education and controlling for survey effects and missing data. (IEOut is measured as standardized regression coefficients. The local polynomial smooth has a span of .65 and uses weights proportional to the inverse of the variances.)

(a) A priori scale
(b) Empirical scale
(c) Controlled for survey
(d) Multiple imputation
Figure 8: Trend in Inequality of Educational Outcomes and change in trend for women while using different scales of education and controlling for survey effects and missing data. (IEOut is measured as standardized regression coefficients. The local polynomial smooth has a span of .65 and uses weights proportional to the inverse of the variances).
Table 2: Conversion of old educational levels into new educational levels and simplified educational levels

<table>
<thead>
<tr>
<th>level</th>
<th>English translation</th>
<th>ISCED&lt;sup&gt;a&lt;/sup&gt;</th>
<th>institutional duration</th>
<th>a priori scale</th>
<th>empirical scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>LO</td>
<td>primary</td>
<td>1</td>
<td>6</td>
<td>6.0</td>
<td>6.0</td>
</tr>
<tr>
<td>LBO</td>
<td>junior vocational</td>
<td>2C</td>
<td>10</td>
<td>9.0</td>
<td>7.0</td>
</tr>
<tr>
<td>MAVO</td>
<td>junior general secondary</td>
<td>2B&lt;sup&gt;b&lt;/sup&gt;</td>
<td>9 / 10</td>
<td>10.0</td>
<td>10.5&lt;sup&gt;c&lt;/sup&gt; / 9.5&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td>MBO</td>
<td>senior secondary vocational</td>
<td>3C</td>
<td>14</td>
<td>10.5</td>
<td>10.0</td>
</tr>
<tr>
<td>HAVO</td>
<td>senior general secondary</td>
<td>3B&lt;sup&gt;b&lt;/sup&gt;</td>
<td>11</td>
<td>11.0</td>
<td>11.0</td>
</tr>
<tr>
<td>VWO</td>
<td>pre-university</td>
<td>3A&lt;sup&gt;b&lt;/sup&gt;</td>
<td>12</td>
<td>12.0</td>
<td>13.0</td>
</tr>
<tr>
<td>HBO</td>
<td>higher professional</td>
<td>5B</td>
<td>15</td>
<td>15.0</td>
<td>15.0&lt;sup&gt;c&lt;/sup&gt; / 14.5&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td>WO</td>
<td>university</td>
<td>5A</td>
<td>17 / 16</td>
<td>17.0</td>
<td>17.0</td>
</tr>
</tbody>
</table>

<sup>a</sup> (UNESCO, 1997)

<sup>b</sup> These levels were originally intended to be terminal levels of education for most students (so 2C or 3C) but evolved into levels that primarily grant access to subsequent levels of education.

<sup>c</sup> before 1968

<sup>d</sup> after 1968